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The filtering based maximum likelihood recursive least squares estimation for multiple-input single-output systems[☆]

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ABSTRACT

In this paper, we use a noise transfer function to filter the input–output data and propose a new recursive algorithm for multiple-input single-output systems under the maximum likelihood principle. The main contributions of this paper are to derive a filtering based maximum likelihood recursive least squares (F-ML-RLS) algorithm for reducing computational burden and to present two recursive least squares algorithms to show the effectiveness of the F-ML-RLS algorithm. In the end, an illustrative simulation example is provided to test the proposed algorithms and we show that the F-ML-RLS algorithm has a high computational efficiency with smaller sizes of its covariance matrices and can produce more accurate parameter estimates.

1. Introduction

Recursive algorithms have wide applications in many areas such as computational mathematics, system theory, and matrix equations [1–4]. For example, Dehghan and Hajarian proposed an iterative algorithm for solving the generalized coupled Sylvester matrix equations [5]; Hashemi and Dehghan proposed the use of an interval Gaussian elimination to find an enclosure for the united solution set of the interval matrix equation [6]; Dehghani-Madiseh and Dehghan introduced the generalized solution sets to the interval generalized Sylvester matrix equation and developed some algebraic approaches for inner and outer estimations [7].

The study of modeling and identification of multivariable systems has been receiving much attention because most of the realistic physical processes are multivariable systems [8–10]. Recently, there are many estimation methods developed for multivariable systems. For example, Zhang presented a recursive least squares estimation algorithm for the multi-input single-output systems based on the bias compensation technique [11]; Chen and Ding derived a decomposition based maximum likelihood generalized extended least squares algorithm for multiple-input single-output nonlinear Box–Jenkins systems [12].

The least squares algorithms have wide applications in signal processing [13,14], data filtering [15–18], system control [19–22] and system identification [23–25]. For example, Ding et al. proposed a recursive least squares parameter identification algorithms for output-error autoregressive systems [26]; Wang et al. presented a hierarchical least squares algorithm and a key term separation based least squares algorithm for dual-rate Hammerstein systems [27]; Hajarian and Dehghan proposed the generalized centro-symmetric and least squares generalized centro-symmetric solutions for solving a linear matrix equation [28].

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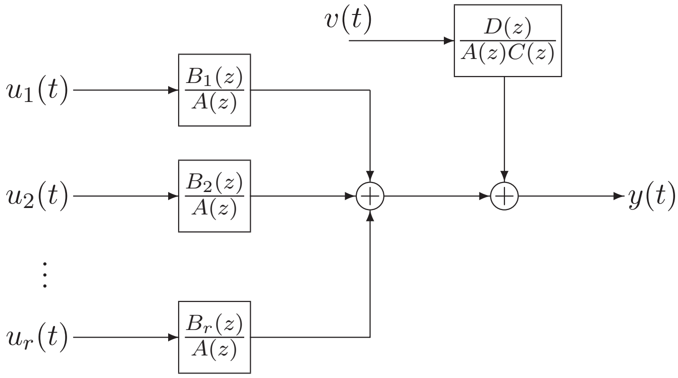

Fig. 1. The multiple-input single-output systems.

In the area of the maximum likelihood identification [29–31], Söderström et al. used the time domain maximum likelihood method and the sample maximum likelihood method to identify the errors-in-variables models under different assumptions and the results showed that these two methods have the same accuracy at any signal-to-noise ratios for output-error model identification [32]; Vanbeylen et al. constructed a Gaussian maximum likelihood estimator and proposed a blind maximum likelihood identification algorithm for discrete-time Hammerstein systems [33]; Chen et al. presented a maximum likelihood gradient-based iterative estimation algorithm for input nonlinear controlled autoregressive autoregressive moving average systems [34].

This paper studies the parameter estimation problem of a class of multiple-input single-output (MISO) systems with colored noise for given model representation with known structure. The identification method reported here is based on the maximum likelihood principle and thus differs from the hierarchical generalized least squares method in [35]. The proposed parameter estimation methods in this paper can be applied to study the modeling of other multivariable systems [36–38].

The outline of this paper is as follows. Section 2 derives a recursive generalized extended least squares algorithm for multiple-input single-output systems. Section 3 gives a filtering based recursive extended least squares algorithm. Section 4 derives a filtering based maximum likelihood recursive least squares identification algorithm and a recursive prediction error method. Section 5 provides numerical simulations to verify the effectiveness of the proposed algorithm. Finally, we offer some concluding remarks in Section 6.

2. The recursive generalized extended least squares algorithm

In this paper, we study the MISO system depicted in Fig. 1 and described by the following equation error model:

$$A(z)y(t) = \sum_{j=1}^{r} B_j(z)u_j(t) + \frac{D(z)}{C(z)}v(t), \tag{1}$$

where $y(t)$ is the system output, $u_j(t)$, $j = 1, 2, \ldots, r$, are the system inputs, $v(t)$ is the uncorrelated stochastic noise with zero mean and variance σ^2, $A(z)$, $B_j(z)$, $C(z)$ and $D(z)$ are polynomials in the unit backward shift operator $z^{-1}[z^{-1}y(t) = y(t-1)]$, and

$$\begin{aligned}
A(z) &= 1 + a_1z^{-1} + a_2z^{-2} + \cdots + a_{n_a}z^{-n_a},\\
B_j(z) &= b_{j1}z^{-1} + b_{j2}z^{-2} + \cdots + b_{jn_j}z^{-n_j},\\
C(z) &= 1 + c_1z^{-1} + c_2z^{-2} + \cdots + c_{n_c}z^{-n_c},\\
D(z) &= 1 + d_1z^{-1} + d_2z^{-2} + \cdots + d_{n_d}z^{-n_d}.
\end{aligned}$$

Assume that the order n_a, n_c, n_d and n_j, $j = 1, 2, \ldots, r$ are known and $y(t) = 0$, $u_j(t) = 0$ and $v(t) = 0$ as $t \le 0$.

Define the inner variable

$$w(t) := \frac{D(z)}{C(z)}v(t), \tag{2}$$

which is an autoregressive moving average process. Let the superscript T denote the transpose and define the parameter vectors $\boldsymbol{\theta}$, $\boldsymbol{\theta}_{\rm s}$, $\boldsymbol{\theta}_{\rm n}$ and the information vectors $\boldsymbol{\varphi}(t)$, $\boldsymbol{\varphi}_{\rm s}(t)$, $\boldsymbol{\varphi}_{\rm n}(t)$ as

$$\begin{aligned}
\boldsymbol{\theta} &:= \begin{bmatrix}\boldsymbol{\theta}_{\rm s}\\ \boldsymbol{\theta}_{\rm n}\end{bmatrix} \in \mathbb{R}^n,\ n := n_a + \sum_{i=1}^{r} n_i + n_c + n_d,\\
\boldsymbol{\theta}_{\rm s} &:= [a_1, a_2, \ldots, a_{n_a}, b_{11}, b_{12}, \ldots, b_{1n_1}, b_{21}, b_{22}, \ldots, b_{2n_2}, \ldots, b_{r1}, b_{r2}, \ldots, b_{rn_r}]^{\rm T} \in \mathbb{R}^{n_a+n_1+n_2+\cdots+n_r},\\
\boldsymbol{\theta}_{\rm n} &:= [c_1, c_2, \ldots, c_{n_c}, d_1, d_2, \ldots, d_{n_d}]^{\rm T} \in \mathbb{R}^{n_c+n_d},
\end{aligned}$$